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HARNESSING THE POWER OF ARTIFICIAL INTELLIGENCE TO IMPROVE MANAGEMENT INFORMATION SYSTEMS

Abstract*: Artificial Intelligence (AI) and its applications have gained immense popularity in the recent months, especially due to the popularity of ChatGPT. This systematic review paper examines the potential of Artificial Intelligence to improve the functioning and effectiveness of Management Information Systems (MIS). The paper reviews current literature and research on the use of AI in MIS and its potential to improve performance, accuracy, and decision making. It examines the challenges associated with the implementation of AI in MIS, such as the need for well-defined algorithms, the ability to integrate with existing systems, and the potential for introducing bias. Additionally, the paper considers the implications of AI on data security and privacy, as well as its potential to reduce costs and increase efficiency. The paper concludes by discussing how AI can be used to create and sustain competitive advantages in the MIS space. The paper provides an overview of the potential benefits and challenges of using AI in MIS, and the potential for AI to revolutionize the way businesses use and manage their information systems.*

Keywords: *Artificial Intelligence (AI), Management Information Systems (Mis), current trends, review*

1. Introduction

Mays Business School defines management information system (MIS) as, “Management Information Systems (MIS) is the study of people, technology, organizations, and the relationships among them. MIS professionals help firms realize maximum benefit from investment in personnel, equipment, and business processes. MIS is a people-oriented field with an emphasis on service through technology.” (Mays Business School, 2023). Thus, it is a fusion of business environment variables and information technology.

According to the definition of IBM (IBM, 2023), the term artificial intelligence (AI) refers to, “a field, which combines computer science and robust datasets, to enable problem-solving. It also encompasses sub-fields of machine learning and deep learning, which are frequently mentioned in conjunction with artificial intelligence. These disciplines are comprised of AI algorithms which seek to create expert systems which make predictions or classifications based on input data.” AI and its applications have gained immense popularity in the recent months, especially due to the popularity of ChatGPT, a chatbot developed by OpenAI.

This paper aims at a systematic review of the applications and usefulness of AI to improve

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MIS. The method followed to select the relevant literature is described below.

2. Methodology

Google Scholar was used as the search engine for identifying the papers related to the topic of review. The search using appropriate search terms indicating the review topic resulted in identifying papers. Using the PRISMA flow diagram (Figure 1), these papers were screened for various inclusion-exclusion criteria. Only the papers published in English were included. Although full-text articles were preferred, abstracts were also included if they contained useful information. The stress was on more recent papers.

These procedures resulted in the final selection of 29 papers. These papers are reviewed in the following sections. A discussion with some quantitative analyses is presented after the results section. Finally, conclusions, some topics for future research and limitations of this review are provided in the last three sections.

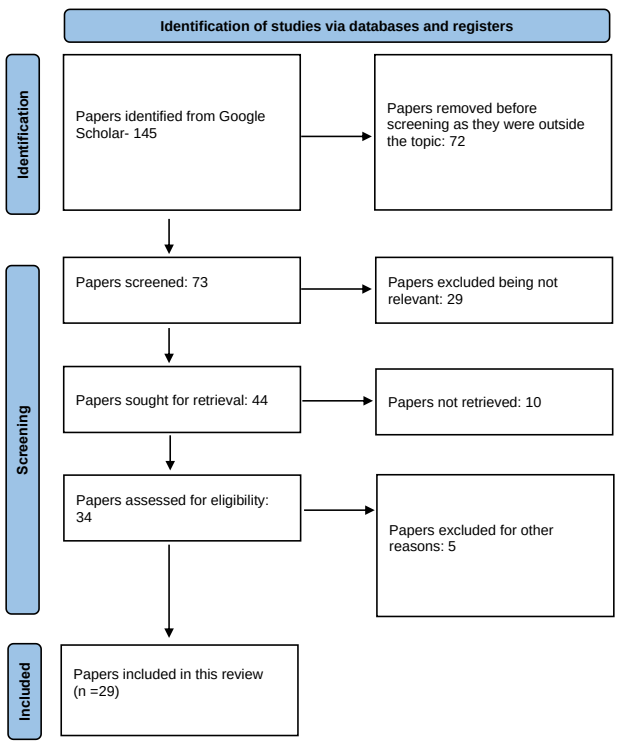

Figure 1. PRISMA flowchart

3. Result

Applications and usefulness of AI in MIS of different sectors and industries are reviewed below.

3.1. General

Wamba-Taguimdje et al. (2020) noted that since 2010, AI has been playing important roles in various business activities due to the development of fast computing algorithms; the availability of cheap graphics processors which can perform large amounts of calculations in milliseconds; and the availability of very large volumes of authentic and reliable data for sophisticated learning of intelligent systems.

AI has introduced a new way of MIS giving both a challenge and an opportunity for organizations. Many business processes constituting part of MIS can now be efficiently handled using AI. Organizations have always wanted to reduce costs and improve efficiencies by transferring human operations to machines. MIS requirements such as solving the problem of analysing rocks in deep layers of the earth facilitated the development plans of the Abu Dhabi National Oil Company (ADNOC). AI also helped United Healthcare Services (UHS) of the USA to streamline its Healthcare Data Management, and Physician Documentation.

AI integration will solve most problems by improving process performance (automated effects, informational effects, and transformational effects) and organizational performance (financial performance, marketing performance, and administrative performance) by generating and analysing MIS data to suggest the best solutions. The usefulness of AI in guiding MIS in different types of organisations for better performance was tabulated by the authors. Fountaine, McCarthy, and Saleh (2019) pointed out that, to use AI in MIS effectively, firms must break organisational and cultural barriers.

To address the challenges in the use of AI for teamwork in projects, Webber, Detjen, MacLean, and Thomas (2019) suggested a multi-step analysis and improvement of teamwork processes.

In a study using electronic databases and Zott's focus as the research methodology, Mendoza, Ortega, Hormaza, and Soto (2020) found that the practices used in the peer assessment processes depended upon the supporting technology within AI used in the learning process.

An integrated AI acceptance-avoidance model (IAAAM) was developed and validated using a survey by Cao, Duan, Edwards, and Dwivedi (2021) to measure the collective influence of both positive and negative factors on managers' attitudes and behavioural intentions towards AI and its use. The model was found to be useful to describe the role of AI in organisational decision-making.

Demigha (2021) explained the difference between DSS/BIS and MIS. A decision support system (DSS) or Business Intelligence System (BIS) is an information system supporting business or organizational decision-making activities. Management information systems (MIS) deal with the development of systems to generate information to improve the efficiency and effectiveness of decision-making. The author studied the implications of both a decision support system (DSS) and a management information system (MIS) in organisations.

To investigate the perception among external auditors toward the contribution of AI to audit quality, and whether AI usage and its impact on audit quality differ between local and international external auditors, Noordin, Hussainey, and Hayek (2022) surveyed 22 local and 41 international audit firms in the UAE. There were no significant differences in the perceived contribution of AI to audit quality between local and international audit firms. All the audit firms, whether local or international, had equal perceptions of AI contributions to audit quality.

The limited sample size was a problem. As the population of the independent variables was unknown, only 63 responses (22 local and 41 international audit firms in the UAE) were obtained.

Five AI applications in the industry were discussed at the IEEE Conference on AI for Applications, 1995. C.W. Liew's "Using Feedback to Improve VLSI Designs" described a new technique called constrained redo that used feedback to improve the power and coverage of an existing system for VLSI design. Typical knowledge-based expert systems are static, incorporating large amounts of domain-specific knowledge to generate good initial solutions. Also, these systems cannot use the information generated from the analysis of the solutions to provide improved solutions. As a result,

the authors used an approach that was part of a feedback-directed optimization framework to generate improved designs.

Chih-Hung Wu and Shie-Jue Lee's "Knowledge Verification with an Enhanced High-Level Petri Net Model" used enhanced high-level Petri nets to model rule-based systems. After modelling the system as a Petri net, their approach used the markings to facilitate verification of the system by determining redundancy, subsumption, conflict, cycles, and unnecessary conditions. In the third paper of Jonathan Lee, Lein F. Lai, and Wei T. Huang's "Conceptual Graphs as a Basis for Expressing Task-Based Specifications," several issues were identified concerning the mapping a task-based specifications methodology into conceptual graphs, including representation of constraints and state modelling, rigid versus soft post conditions, and the distinction and existence of different operators used for modelling specifications.

The authors proposed conceptual graphs to express task specifications and the specifications were driven by the task structure of the problem-solving knowledge. The approach permitted verification of specification representations. Timothy Lenz, James K. McDowell, Martin C. Hawley, Ahmed Kamel, and Jon Sticklen titled their paper, "A Decision Support Architecture for Polymer Composites Design: Implementations and Evolution." In this multidisciplinary study, an architecture for a knowledge-based system for polymer composite material design was developed. The authors used the generic task approach to develop an intelligent support system for polymer design.

They traced the evolution of multiple systems designed to assist decision-making and contrasted the different versions of the systems. James Mayfield, Marty Hall, and Tim Finin's paper "Using Automatic Memoization as a Software Engineering Tool in Real World AI Systems" describes how memoization could be made viable on a large scale. Memo functions and memoization refer to the tabulation of results of a set of calculations to avoid repeating the calculations. Automatic memoization refers to a method by which a function can be changed mechanically into one that memoizes or caches its results. The authors described many advantages and use of automatic memoization, not previously described and identified components of an automatic memoization facility (O'Leary, 1996).

According to Wilson, James, and Daugherty (2018), AI should augment the decision-making system rather than replace it to get the highest benefits. Smart machines and people need to collaborate in a pre-determined manner. For this, these machines need to be especially trained, Companies need to reengineer their business processes, focusing on using AI to achieve more operational flexibility or speed, greater scale, better decision-making, or increased personalization of products and services, all leading to higher performance. Examples of using such collaborations for decision-making include equipment maintenance at General Electric, financial services at Morgan & Stanley, and disease prediction at Icahn School of Medicine at Mount Sinai. AI can detect invisible problems like unknown unknowns by finding causal relationships between variables in massive data. Other uses of AI in decision-making are rapid and accurate detection of credit card frauds and initial screening processes of HR recruitments to narrow down to the very few most suitable for personal interviews. However, these new collaborations need to train the employees also appropriately.

Knowledge-based entity prediction (KEP) is a novel task that aims to improve machine perception in autonomous systems. KEP leverages relational knowledge from heterogeneous sources in predicting potentially unrecognized entities. After proposing a definition for KEP (KEP is the task of predicting the inclusion of potentially unrecognized entities in a scene, given the

current and background knowledge of the scene represented as a knowledge graph), Wickramarachchi, Henson, and Sheth (2022) introduced three potential solutions, employing many data mining and machine learning methods. The applicability of KEP was demonstrated using two systems: autonomous driving and smart manufacturing.

3.2. Government Institutions

The results of a survey of current government employees by Ahn and Chen (2022) revealed that their willingness to support AI in the government varied with their perception of how AI can improve the efficiency of the work and a longer-term outlook on AI's future regarding human labour (as an assistant or a competitor), the perception of the technology's ultimate harm or benefit to the humanity, its ability to eventually make ethical and moral judgments.

Technologies like AI are increasingly altering how the decisions are made by government agencies or the pressures for government agencies to do more with fewer resources. Two legal and regulatory issues arise concerning the implementation of such automated decision-making by government institutions. It needs to be ensured that automated decision-making systems (AI-facilitated systems) are designed and implemented in compliance with existing legal requirements. For this purpose, either modification of current legal requirements or supplementing them with new guidelines, or even both, may be required. The second issue is related to ethical and policy issues when some human functions are delegated to machines (Paterson, 2019).

The objective of the study by Behl, et al. (2021) was to evaluate the readiness of government agencies to adopt artificial intelligence (AI) for the improvement in the efficiency of disaster relief operations (DRO) in India. For understanding the behaviour of state-level and national-level government agencies involved in DRO, the civic volunteerism model was used along with the commonly used unified theory of acceptance and use of technology (UTAUT). Apart from the collection of primary data from the DRO agencies, a survey of 184 government employees was done. Partial least square-structural equation modelling was used for testing hypotheses. The significant influence of resources (time, money, and skills) on the behavioural intentions related to the adoption of AI tools for DRO was noted. Positive translation of these behavioural intentions into actions to adopt AI tools was also observed.

The relationship between the use of AI and value creation from the perspectives of citizens has not been understood fully. Grounded on Moore’s public value management, Wang, Teo, and Janssen (2021) evaluated the relationship and value creation in the Chinese public sector. Public service value was categorised into public value and private value between AI use. The indicators used for public value were procedural justice and trust in government. Based on motivation theory, perceived usefulness and perceived enjoyment were used as indicators of private value. The responses obtained from a field survey of AI voice robot users showed that the effective use of AI voice robots was related to private value and procedural justice. On the other hand, no relationship was found between the effective use of AI and trust in government. Contrasting with the common idea that value creation from the government should focus on social objectives related to the public value that is more important to citizens, the private value had a greater effect on overall value creation than public value. There were variations in AI usage behaviours due to gender and experience.

3.3. Healthcare

While AI has been increasingly being used for advanced clinical decision support systems (CDSS), there are various pressures

between an AI-CDSS system ("Brilliant Doctor") and its implementation in the rural clinical context. These pressures include the misalignment with local context and workflow, the technical limitations and usability barriers, transparency, and trustworthiness of AI-CDSS. However, most of the clinicians interviewed by Wang, et al. (2021) supported the implementation of the system.

In healthcare management, human-AI interactions may vary depending on human factors like expectancy, workload, trust, cognitive variables related to absorptive capacity and bounded rationality, and concerns for patient safety. Choudhury (2022) proposed framework leverage this relationship to identify factors influencing clinicians' intention to use AI and improve AI acceptance so that the lack of AI accountability to safeguard the patients, clinicians, and AI technology can be addressed. A few limitations of this study were discussed by the authors.

For the effectiveness of healthcare decision-making for high quality, AI could be used. According to Choudhury and Asan (2022), this will require the consideration of human factors. The authors used a semi-structured survey of US clinicians' perceptions of the role of accountability, training, and their impact on the intention of using AI and associated decision-making and the role of AI on workload, trustworthiness, risk, and performance expectancy. The analysis of 265 responses using sequential regression and inductive content for quantitative and qualitative information showed a significant impact on perceived workload, perceived trustworthiness of AI, perceived risk of AI, and willingness to receive AI training on using AI. The lack of AI accountability was an inhibiting factor in AI use. The performance expectancy, perceived risk, and trustworthiness influenced practitioners' perceptions of the impact of AI on decision-making.

The attempts to use an AI algorithm for the prediction of patients missing hospital appointments by Iacobucci (2019) were judged to be not very precise as it incorrectly identified around half of the patients who attended appointments as being at risk of not attending them.

Technological developments in emerging AI technologies are assumed to further routinize and improve the efficiency of decision-making tasks, even in professional contexts such as medical diagnosis, human resource management, and criminal justice. There is little research on how AI technologies are used and adopted in practice. Most research focused on the gaps between the expectations for new technology and its actual use in practice. Lebovitz (2019) undertook a comparative field study at three sections in the Department of Radiology in a major US hospital, whereby new and existing AI tools were being used and experimented with. In contrast to expectations, the AI tools transformed routine professional decision-making tasks into nonroutine ones, as they increased ambiguity and decision-makers had to work to reduce it. This was particularly challenging as the costs of dealing with ambiguity, in terms of increased time to diagnose, were often weighed against the benefits of such ambiguity leading to potentially more precise diagnoses.

AI-based clinical diagnostic decision support systems can improve doctors' efficiency and accuracy leading to better healthcare quality. But their level of adoption remains quite low, threatening their success due to inadequate uptake of the innovation. Prakash and Das (2021) used a mixed approach to develop a model based on theories of Unified Theory of Acceptance and Use of Technology, status quo bias, and technology trust and testing the model to identify the factors related to this condition. Performance expectancy, effort expectancy, social influence, initial trust, and resistance to change predicted intention to use. Inertia, perceived threat, and risks (medico-legal and

performance) determined resistance to change. Methods to deal with resistance and improve adoption rates were proposed.

3.4. Hospitality Sector

Analysing user-generated content for its usefulness in decision-making by tourists and tourism organisations, Akehurst (2009) observed that the high cost, energy, resources and costs and long time required to locate relevant user-generated content and extract useful and meaningful information has led to the search for automated tracker systems utilising artificial intelligence. If the search is successful, tourism-related organisations and tourists will have a highly powerful new method for decision-making.

Aiming to investigate the AI service recovery in the hospitality industry, Lv, Yang, Qin, Cao, and Xu (2022) shifted from the traditional "intelligence quotient" thinking and explored the recovery effect of empathy response from the emotional intelligence perspective. For this, four experimental scenarios were used. Study 1 examined the effect of AI empathic response on consumers' intention to continue using AI services as outcome failure in Part 1 and process failure in Part 2. Study 2 examined whether an empathic response of AI would evoke consumers' continuous usage intention through psychological distance and trust and whether the sequentially mediated effect worked in both types of service failure. Study 3 examined whether the effect of AI empathic response on consumers' continuous usage intention would be moderated by the interaction modality in two types of service failure. The contexts of the four scenarios were different. The results indicated that, in service recovery, a high-empathy AI response can increase the continuous usage intention of customers, and psychological distance and trust mediated this process. Compared to mono-sensory stimulus interactions involving text only, a high-empathy response with multisensory stimulus interactions (text and voice) was better in strengthening the recovery effect of empathy responses. Thus, the field of AI service research from a focus on time and phase was extended to the continuing use of AI after service failure in this paper. The paper provides a useful tool for resolving AI service failure problems autonomously in the service process, which is very useful for research and hospitality operators in the promotion and application of AI services. One limitation of this study was that the experimental scenarios used in this article were limited to cases where the degree of failure was low. This is because the current frontline AI services undertake only certain simple tasks in which failure generally does not cause large losses to customers. As a result, customers do not regard the failure of AI services seriously.

3.5. Production system

AI can assist predictive maintenance of renewable energy systems by inspectors using image-based sensors. A case study was conducted by Shin, Han, and Rhee (2021) for predictive maintenance of wind farms. Endoscopic images were used for bearing fault detection. In the experiment, 54 technical inspectors were asked to examine 2301 images collected over 138 wind turbines and to identify bearing faults in the absence and presence of AI assistance. Specificity and time efficiency was improved by AI assistance, the level of improvement depending on their expertise. Generalists showed greater improvement than specialists. Both groups were interested in the continued use of AI. Limitations related to cognitive load and the relationship between human and AI performance have been discussed.

To answer the research question, how does manufacturing incumbents use AI for enabling business model innovation in industrial ecosystems, Burström, Parida, Lahti, and Wincent (2021) used qualitative method to study four large global manufacturing incumbents using AI to

transform their business models. More than 30 semi-structured in-depth interviews were conducted with strategic key personnel for this purpose.

The results showed the need for AI business-model innovation to be aligned with ecosystem innovation. Successful manufacturing incumbents performed AI-enabled business-model innovation in a dynamic way, where various AI functionalities impacted value-creation, value-delivery, and value-capture processes. The analysis also showed that incumbents typically developed AI solutions in global networks consisting of interdependent partners, complementors, suppliers, and customers.

3.6. Financial Institutions

In a Vietnamese study on its banking systems, Van Thuy (2022) stressed the role of the internet of things (IoT) and reliable internet data for the sustainability of banking systems. Regression models constructed using statistical software can help in the improvement of MIS in banking systems. Digital technology can facilitate the building of reliable internet data for these purposes.

3.7. Marketing and Communications

The usefulness of AI for high-quality marketing decisions was discussed by Goel and Tiwari (2020). If marketing data could be organised and analysed appropriately, business firms can be aggressive. AI facilitates this through MIS, in which marketing data are also included.

Under the background of the information economy, user pressure is created due to the fragmentation of time and information in the social media of electronic business platforms of advertising information. However, the enterprise push mechanism of artificially intelligent information and no classification for these users leads to user pressure on processing information every day, which affects the user's mood. Then users are to exit from using these applications. In the context of the internet economy, the push mechanism and big data algorithm of enterprises indirectly affect users' willingness to use. The key issue is how to use AI to carry out more accurate marketing and information promotion.

In this respect, Liu (2022) found that enterprises can classify and batch users and use AI for better judgement of the current social burnout of users, and then moderately push information to users. Integrating this with the internet economy and information economy, it can be used as a reference for enterprises to manage themselves and conduct precision marketing better to match users' needs with information processing ability.

In a review of AI applications in optical communications technologies, Mata, et al. (2018) showed that the desirability of AI applications using different algorithms in this area has been demonstrated in many aspects. Specifically, about optical transmission, AI tools are suitable when dealing with the characterization and operation of transmitters, EDFAs and receivers, performance monitoring, mitigation of nonlinearities, and for QoT estimation, which is particularly relevant in impairment-aware optical network operation. The AI applications range from optical network planning to connection establishment as a pursuit of the optimal solution for the RWA, RSA, RMLSA or RMCSA problems), network reconfiguration, software-defined networking and applications in specific types of networks such as OBS networks, Passive Optical Networks and data centres. Some issues and challenges have also been discussed. Attack and intrusion detection seems to be a less researched area, needing urgent focus.

3.8. Customer relationship management

The rapidly increasing customer demands have necessitated the need for ECRM,

leveraging the technological advancements in MIS and its applications. Abdulla (2022) discussed tracking and maintaining ECRM using big data analytics tools and AI algorithms. The predictions and forecasts a business make based on consumer behaviour have been explained. The various avenues of AI have also been dealt with. The taxonomy of AI and its decision-making capability was applied to design and simulate effective SCM systems. Various AI methods were holistically applied to the FMCG supply chain context.

The role of big data analytics in maintaining ECRM by studying consumer preferences and choices has been explored in the context of maintaining the FMCG supply chain. This research report also discusses various methods of AI used in the supply chain and the data analytics tools employed in maintaining ECRM and the FMCG supply chain.

Connected business ecosystems determine the new business challenges in the B2B sector. Data-driven decision-making is critical for successful B2B strategies. As digital marketing is increasingly being used for both communication and sales, the use of Customer Management Relationship (CRM) systems to precisely manage firm information has become important. Research focused on the understanding and application of AI technologies in B2B digital marketing is rare. This gap was addressed by Saura, Ribeiro-Soriano, and Palacios-Marqués (2021) through a systematic literature review. The outcomes of the literature review were measured using a statistical approach known as Multiple Correspondence Analysis (MCA) under the homogeneity analysis of variance using alternating least squares (HOMALS) framework programmed in the R language.

Three typologies of AI-based CRM functionalities have been recognised: analytical CRM, operational CRM, and collaborative CRM. The authors have tabulated the functions of the three typologies. The 34 papers selected for the review were also classified into these categories. The limitations of the research are the limited number of samples, especially considering the statistical analysis done. The databases used and the extent of depth in the selected papers are other limitations. Visual interpretation of results using the MCA method itself can be a limitation.

4. Discussion

Overall, the reviewed papers reflected large-scale applications and the usefulness of AI in different MIS contexts. However, as was pointed out by Lebovitz (2019), there is little research on how AI technologies are used and adopted in practice. The distribution of papers according to sectors or industries is presented in Fig 2.

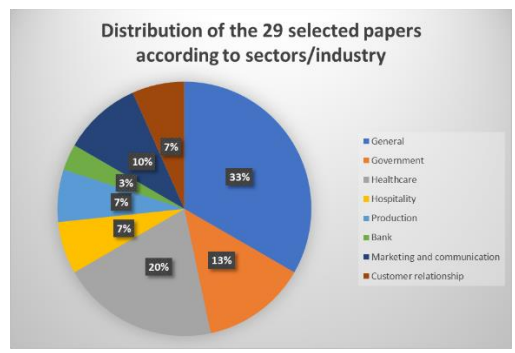

Figure 2. Distribution of the 30 selected papers according to sector/industry

As is evident from Fig 1, papers of the general category, which cannot be classified into specific sectors or industries, dominated (33%) among the selected papers. Among specific sectors, healthcare had the highest (20%) papers. There was a high percentage of (13%) papers related to AI in the government sector. The year-wise distribution of the 29 selected papers is presented in Fig 3.

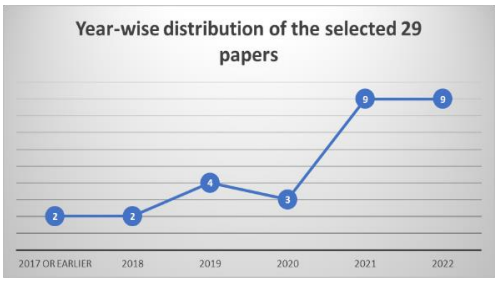

Figure 3. The year-wise distribution

The maximum number of nine papers each were published in 2021 and 2022. Papers published in 2018 were four. There was no paper published in 2017 or earlier, other than one each in 2009 and 1996. The distribution of the 29 selected papers according to the type of paper, is shown in Fig 4.

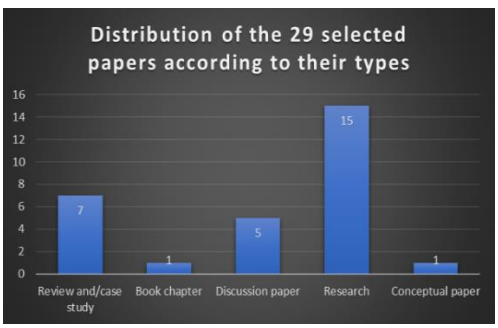

Figure 4. Distribution of the 29 selected papers according to their types.

The data in Fig 3 shows that the maximum number of papers (15) were research papers. There were seven reviews with case studies or some research data. Discussion papers numbering five could also be considered reviews. Researchers are trying to understand and test various AI tools for use in MIS in different contexts, rather than just reviewing past work only.

5. Conclusion

From the above review and the analysis of papers, it is clear that researchers are actively engaged in finding new AI tools, and new ways of using AI tools and extending their usefulness in different aspects of MIS. This is particularly evident in the case of the healthcare sector. In this sector, any error from the AI tools or the healthcare professional can lead to disastrous outcomes. Hence, rigorous testing of AI tools is required.

More work on the application and usefulness of innovatively designed AI tools and methods is required. However, AI tools should collaborate with humans and not replace them, as was noted by Wilson, James, and Daugherty (2018). There is also a great need to focus on the outcomes of using AI tools in various contexts. Scarcity in this aspect was pointed out by Lebovitz (2019).

5.1 Limitations

Only 29 papers could be selected from seven pages of Google Scholar. This is due to the stress given on more recent works, although some earlier seminal papers have also been included. Undoubtedly, many more papers have been published, which deserve to be included in a more detailed systematic review. There are other ways of categorising the papers than what is used here. The method used here was highlighting the current status of information in a particular sector or industry.

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